MULTINATIONAL COMPANIES AND PRODUCTIVITY SPILLOVERS: A META-ANALYSIS

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Abstract

This paper presents a meta-analysis of the literature on multinational companies and productivity spillovers. By collecting information from a sample of published and unpublished papers on the impact of multinational presence on domestic productivity we investigate whether certain aspects of the study design affect the results, and whether there is publication bias in the literature. Our findings show that some aspects of the empirical methods used, namely, how the presence of multinationals is defined, and whether cross-section or panel analysis is employed, may have an effect on the results. We also discover some evidence that there may be publication bias.

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The increasing importance of multinational companies (MNCs) and associated foreign direct investment (FDI) for international production has prompted considerable interest in the effects of MNCs on host countries.[1] One of the most frequently referred to positive effect is the presence of technological externalities, which can lead to productivity spillovers from MNCs to domestic firms in the host country. Since MNCs use a higher level of technology, and technology, or knowledge, has certain characteristics of public goods (see Caves, 1996, Markusen, 1995), there is scope for technological externalities and indigenous firms may benefit through spillovers from MNCs. If there are productivity spillovers, the presence of MNCs leads to productivity increases in domestic firms, allowing them to become more efficient.[2]

Such spillovers can occur through three main channels (Blomström and Kokko, 1998). Firstly, if there are movements of highly skilled staff from MNCs to domestic firms, these employees may take with them knowledge which may be usefully applied in the domestic firm. Secondly, there may be so-called "demonstration effects" if there are arm's-length-relationships between MNCs and domestic firms and domestic firms learn superior production technologies from multinationals. Thirdly, competition from multinationals may force domestic rivals to up-date production technologies and techniques to become more productive. This is frequently referred to as a "competition effect". As Aitken and Harrison (1999) point out, however, this competition effect may also reduce productivity in domestic firms, if MNCs attract away demand from their domestic competitors.

[1] There is also a literature concerned with examining the effects of MNCs on home countries, see, for example Blomström et al. (1997). As this is not the focus of our paper we do not review these issues herein.

Productivity spillovers are difficult to measure, since, as Krugman (1991, p. 53) points out, "knowledge flows […] leave no paper trail by which they may be measured and tracked". The approach adopted in the empirical literature therefore largely avoids the (arguably difficult to answer) question as to how productivity spillovers actually take place, but focuses on the simpler issue of whether or not the presence of multinationals affects productivity in domestic firms. This is usually done in the framework of an econometric analysis in which labour productivity or total factor productivity in domestic firms is regressed on a number of covariates assumed to have an effect on productivity, one of which is the presence of foreign firms. If the estimate of the coefficient on the foreign presence variable turns out to have a positive and statistically significant sign, this is taken as evidence that spillovers have taken place from MNCs to domestic firms.

The empirical results on the presence of spillovers are mixed. In the first empirical study of this kind, Caves (1974), using cross-sectional data for Australia finds evidence of positive spillovers. His initial approach has been refined and extended subsequently by, for example, Globerman (1979) for Canada, and Blomström and Persson (1983), Blomström (1986), Blomström and Wolff (1994) and Kokko (1994, 1996) using data for Mexico. These studies, all of which use cross-sectional data, also find statistically significant positive effects of the presence of multinationals on productivity in domestic firms. Haddad and Harrison (1993) appear to be the first paper which benefits from the availability of firm level data for several years, and newly developed panel data econometric techniques to analyse productivity spillovers from multinationals in Morocco. Using such highly dis-aggregated data and the appropriate estimation

[2] See Blomström and Kokko (1998) and Pack and Saggi (1997) for recent concise reviews of the literature

techniques they find evidence for negative spillover effects of multinationals, i.e., all other things equal, the presence of multinationals in Morocco reduces productivity in domestic firms.

Table 1 lists the results of our literature search, described in more detail in the next section, on papers on productivity spillovers from multinationals. It is apparent that, while there have been a number of spillover studies since Caves (1974), recent years have seen a surge of such studies. This reflects, on the one hand, the growing interest, not the least from policy makers, in the effects of multinationals on host countries in order to justify policy incentives aimed at attracting multinationals. On the other hand, it also bears testimony to the fact that dis-aggregated data over longer time periods and estimation techniques for the analysis of such data allowing the investigation of this issue have become widely available to researchers. One should note from the table that, since Kokko et al. (1996) all but two studies listed had available firm level data. Also, the table shows that all but one study using panel data find statistically significant negative or statistically insignificant effects of MNC presence on domestic productivity, while all but one cross-sectional study find statistically significant positive effects. This suggests that the availability of longitudinal firm level data, and the appropriate statistical techniques for analysing them, have had profound effects on the results obtained in spillover studies.

Table 1 here

Various explanations are put forward in the literature to explain statistically insignificant or negative results. For example, the presence of foreign firms can reduce productivity of domestic firms, as pointed out by Aitken and Harrison (1999). Since

on host country effects, in particular, productivity spillovers and technology flows, of MNCs.

foreign firms can frequently be assumed to posses some sort of firm-specific assets (Caves, 1996) which allow them to use a superior production technology, they have lower marginal cost than a domestic competitor and can attract demand away from domestic firms. Thus, productivity in domestic firms falls, at least in the short run, because of competition with multinational companies.

It is also argued in the literature that positive spillovers only affect a certain group of firms and aggregate studies may, therefore, underestimate the true significance of such effects. Kokko et al. (1996) find evidence for productivity spillovers only to domestic firms with moderate technology gaps *vis-à-vis* foreign firms, i.e., domestic firms with at least some capability of being able to make use of the spillover effects. They do not find evidence for spillovers from MNCs to domestic firms which use considerably lower levels of technology. Aitken and Harrison (1999) find that productivity in small Venezuelan firms (with less than 50 employees) has increased following the presence of MNCs, while there does not appear to be a similar effect on large domestic firms.

The question remains unanswered, however, as to why some studies find positive, while others find negative or no spillover effects from multinationals, and why the magnitude of regression coefficients differs across studies. As argued above, differences in research design, methodology and data may have an impact on the results obtained. In this paper we try to shed some light on this issue by performing a meta-analysis of the literature on productivity spillovers. Meta-analysis can be used to summarise, and to explain variations in results of a number of similar empirical studies concerned with one research topic (Stanley and Jarrell, 1989). While meta-analysis has been frequently applied in educational, psychological and medical research,[3] its application in economics has been limited to a relatively small number of studies. For example, Phillips (1994) examines the effect of education and farmers' efficiency, Phillips and Gross's (1995) analysis focuses on the impact of taxes on economic development, Smith and Huang (1995) examine the relationship between willingness to pay for reductions in air pollution, and the level thereof, while Stanley (1998) uses meta-analysis to investigate empirical studies of the Ricardian equivalence theorem. Meta-analysis can also be used to test for publication bias in the literature, that is the tendency in academic journals to publish results which are statistically significant. Such analyses were recently carried out by Card and Krueger (1995) for minimum-wage studies, and Ashenfelter et al. (1999) for papers on the estimates of returns to schooling.

One of the possible reasons why meta-analysis has not been used more frequently in economics may be that the nature of the data used in economic research is, in most cases, non-experimental, while data in the fields of education, psychology or medicine are mainly based on experiments. It may therefore be difficult to transfer many of the methods used in those fields into economics, as results obtained in different economic studies of one topic may be dependent upon each other. As Stanley and Jarrell (1989) argue, however, the problem of dependence of observations is likely to be no more important (or unimportant) for meta-analyses than for primary econometric studies, as those are not the result of controlled experiments either.

Be that as it may, meta-analysis, despite its limitations, can provide a useful tool to analyse the literature on productivity spillovers. Specifically, it allows one to quantify

[3] See Glass et al. (1981), Hunter et al. (1982) and Egger and Smith (1997) for introductions to meta-analysis

and disentangle certain trends in the empirical results that would be difficult to gauge from simple eyeballing. We acknowledge, however, that there are potential problems which ought to be kept in mind when interpreting the results of this paper.

Following Card and Krueger (1995), we employ meta-analysis in the following fashion: For a sample of studies of productivity spillovers, we collect the different coefficients on the foreign presence variable found in the different studies, and their associated values of the *t*-statistic. We then regress the *t*-statistics on a number of meta-independent study characteristics, such as sample size, variable definitions used, etc.; a technique named by Stanley and Jarrell (1989) as "meta-regression analysis". Some of these study characteristics, namely, whether it is a cross-section or panel analysis, and variable definitions have an effect on the size of the coefficient found in the productivity studies. Thus, our analysis suggests that the research design is crucial for a proper analysis of productivity spillovers. Estimating a different specification of the meta-regression, we also find evidence that there may be publication bias in the literature on productivity spillovers.

The remainder of this paper is structured as follows. Section 1 presents the sample of studies used and Section 2 provides the results of the meta-regression analysis. In Section 3 we describe the results of an analysis of publication bias, and Section 4 summarises our main results and presents some concluding comments.

1. Description of the Sample

The sample of papers from the productivity spillovers literature analysed in our paper consists of 21 studies, 18 of which are published in academic journals, one is a

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in the three respective fields.

contribution to an edited volume, and two are unpublished manuscripts (see Table 1 for a listing of studies included). The papers were obtained from inspection of the recent concise survey of the literature of the wider area of technology spillovers by Blomström and Kokko (1998) as well as an EconLit search for the key words "productivity spillovers".[4] Furthermore, we searched through recent issues of appropriate journals and conducted internet searches for unpublished papers. There may, no doubt, be further published and unpublished papers, and especially dissertations which we were not able to take account of in this study. Of the papers included, nine are concerned with measuring productivity spillovers in developed countries (three for the UK, one for Australia, Canada, Czech Republic, Portugal, Spain, and Taiwan). The remaining papers deal with developing countries, five of which examine the Mexican case. All studies relate to manufacturing industries.

In terms of the research design, most studies analyse data for one year, or one specified time period, using one particular definition of the dependent variable and varying the number and definition of explanatory variables reported in the regression results. For such studies, we included in our sample the most preferred specification, either by examining the highest R-squared value or by the comparability of the variable definitions to the other studies included. There are, however, three papers for which we include more than one regression result in the sample. From Sjöholm (1999a) we include three results, since he examines different time periods and uses different definitions of the dependent variable, and from Haddad and Harrison (1993) and Girma et al. (2001) we

[4] The EconLit search produced 171 references, most of which, however, were concerned with the related, yet distinct, issue of R&D spillovers and growth. See, for example, Griliches (1998) for a discussion. Also, we only included papers written in English in our meta analysis.

include two results each to account for their different dependent variable definition. This leads to a total of twenty-five observations to be used in our meta-analysis.

Fourteen observations (from twelve papers) are obtained from studies which used plant level data, while eleven observations relate to industry level data (at varying levels of aggregation). Panel data were only used in eight papers, from which we obtained ten observations, while the remaining studies are based on cross-section data. In terms of the variable definitions, nine observations relate to foreign presence being measured as employment share in foreign owned firms, nine measure foreign presence as output (or value added) share while the other seven use other related measures. Haddad and Harrison (1993), Chuang and Lin (1999) and Djankov and Hoekman (2000) measure foreign presence as the share of assets held by foreign firms, Aitken and Harrison (1999) use the share of foreign equity participation, while Kathuria (2000) uses the share of sales of foreign firms. Driffield (2001) calculates the growth of sales in foreign-owned firms as a measure of foreign presence.

Of the observations included in our sample, 14 out of the 25 cases define the dependent variable as labour productivity (i.e., output or value added per worker), while output growth is used in nine cases. Blomström (1986) calculates a different measure, namely, an efficiency index $e_i = \overline{y_i} / y_i^{+}$ where y_i^{+} is value added per employee in firms in a size class with the highest value added per employee within an industry *i*, and $\overline{y_i}$ is the industry average. Thus, this index calculates the distance of the industry average from the "best practice" or "efficiency frontier" in the industry. Kathuria (2000) uses a similar measure in his study of productivity spillovers in India.[5]

2. Meta-Regression Analysis

In order to attempt an explanation of the variations in results across the sample of studies of productivity spillovers, we follow Stanley and Jarrell (1989) who suggest estimating an equation as follows:

$$Y_j = \beta_0 + \sum_{k=1}^{K} \beta_k Z_{jk} + e_j, \qquad j=1,2,\ldots N \tag{1}$$

where Y_j is the reported estimate in study j from a total of N studies, and Z_{jk} are meta-independent variables which proxy characteristics of the empirical studies in the sample in order to explain the variation in Y_js across studies.

It must be pointed out that an analysis of the differences in the effect of spillovers across studies is hampered by the fact that the foreign presence variable is measured in different units in the different studies. For example, Globerman (1979) measures value-added per worker in thousands of Canadian dollars, while Flores et al. (2000) use millions of Portuguese escudos. Of course, these differences in measurement will affect the magnitude of the coefficients on foreign presence. We, therefore, decided to use a dimensionless variable, namely the *t*-statistic (which can take on positive as well as negative values) as the dependent variable in our meta-analysis, as suggested by Stanley and Jarrell (1989). The *t*-statistic provides us with a standardised measure of the effect of

[5] In some of their specifications, Aitken and Harrison (1999) also use a different dependent variable definition, namely the log of output. In that case, however, both the dependent and the foreign presence variable are defined differently and we therefore do not include this result in our meta-analysis.

the foreign presence variable on the dependent variable which allows a cross-study comparison.

In terms of the choice of explanatory variables to be included in the estimation of equation (1) we are confronted with two main problems. First, there is no economic theory to guide us for our empirical specification, and, second, we are constrained to use a small number of explanatory variables due to a small number of degrees of freedom. Given these constraints, there are a number of characteristics of individual studies which we feel may, a priori, impact on the size of the *t*-statistic. For example, results may differ because of differences in numbers of observations used in the papers. In our sample, the smallest number of observations was available to Blomström and Wolff (1994) with only 20 observations, while Aitken and Harrison (1999), on the other side of the scale, can avail of 32,521 observations. All other things being equal, an increase in the sample size should raise the (absolute value of the) *t*-ratio. To take account of differing sample sizes we include the square root of the degrees of freedom in our meta-analysis, as in Card and Krueger (1995). As we discuss in more detail below, this variable also allows us to conduct a simple test for publication bias in the studies on productivity spillovers.

We also control for differences in the time periods used in the studies by including the average year of the study period. We take account of the nature of the data used by including dummies to control for whether data are industry or plant level, and whether they are cross-section or panel data. Furthermore, we calculate a set of dummies to take account of different definitions of the foreign presence variable (measured as either employment share, output share, or other) and of the dependent variable (output per worker, growth of output, or other). Ideally, we would also like to include country specific dummies; however, given our sample size this was not feasible. To control for differences across host countries we instead include a dummy variable which is equal to one if a country is a developing country and zero if it is developed.

Furthermore, without constraints, it would appear reasonable to include a variable to control for the nature of the different explanatory variables included in the different studies. Again, however, the small size of our sample prevents the inclusion of additional dummy variables to control for this. Suffice it to say that most studies include additional sectoral characteristics as explanatory variables, such as, measures of market concentration (Blomström, 1986), average capital-labour ratio in domestic firms (Kokko et al., 1996), measures of labour quality (Globerman, 1979), or measures of labour and capital inputs in estimations of total output growth (Haddad and Harrison, 1993).

The results of the meta regression, using OLS are reported in Table 3. As Stanley and Jarrell (1989) point out, since the dependent variables are drawn from studies with widely different characteristics, it is highly likely that the error terms of the meta-regression are not homoskedastic. Furthermore, since we use multiple estimates from three papers the error terms from observations taken from the same papers will most likely be correlated. In order to take account of this we calculate standard errors which allow for heteroskedasticity and a non-specified correlation between observations from the same group (i.e., paper).[6] Columns (1) to (4) present estimation results for the total sample, while columns (5) to (8) produce results based on a sample in which we excluded two spillover results which appear to be outliers. We eliminated these two observations, namely one of the results reported by Sjöholm (1999a) and the result by Chuang and Lin

[6] We refer to these as heteroskedasticity-autocorrelation consistent standard errors. See Newey and West

(1999), from our sample as they have what appear to be excessively high *t*-statistics compared to the other studies.

Table 2 here

Our results suggest that studies which use cross-sectional data tend to have, on average, higher *t*-ratios than panel studies. In other words, the effect of productivity spillovers appears to be higher in cross-sectional studies. Although we already pointed out above that none of the cross-sectional studies finds a negative result, while most panel data studies do not find positive results, it is interesting to note that this finding is also true when controlling for other characteristics of the research design.

This difference across data set types may arise because of the problems associated with unobserved time invariant effects. Specifically, if there are time invariant effects across the individual units (either industry or firms) that are not captured in the explanatory variables but are correlated with the foreign presence variable then the cross-sectional studies may produce biased and inconsistent estimates of the effect arising from spillovers. Such time invariant effects may, however, be purged from panel data studies if, for example, a fixed or random effects estimation technique is used (see Baltagi, 1995).[7] Of course, there may be other aspects of the studies, such as mis-specified dynamics or time variant unobservable variables that differ across the cross-sectional and

(1987) for a discussion on the calculation of a covariance matrix with such properties.

[7] Related to this point is the argument put forward by Aitken and Harrison (1999) that, if foreign multinationals gravitate towards more productive sectors there may be a positive association between sectoral productivity and the presence of foreign firms even without spillovers taking place. They find in their study of a panel of Venezuelan firms that including industry dummies changes a positive and statistically significant coefficient to be negative and significant. However, this lack of industry dummies cannot explain the differences in the results for the sample of observations we use, as we have collected results for econometric specifications without dummies for all but one (Blomström and Sjöholm, 1999) study.

panel studies that we are failing to control for. However, despite meticulous checking no such pattern became apparent.

In terms of variable definitions, it does not appear to make a difference how the dependent variable is defined; whether it is output per worker, output growth, or another measure. Our results suggest, however, that the choice of foreign presence proxy may be an important determinant of differences across studies. Including separate dummy variables for whether a study used foreign output share or some other variable to proxy foreign presence, we find that the latter proxy produces lower results relative to our base-line category of foreign employment share. The coefficient on that variables is, however, only statistically significant if we exclude the two outlying observations (i.e., columns (5) to (8). This may suggest that a proper definition of the variable which is supposed to capture the spillover effect is important. As pointed out above, most studies use either the share of employment in foreign-owned firms, or the share of output produced by these firms, as a proxy to capture this effect. Some studies, however, use other measures and our results show that these studies find lower spillover effects than others, ceteris paribus. This raises the question for empirical studies of how to measure foreign presence properly.

Our findings suggest that it does not appear to matter whether a study uses industry or plant level data, whether a study is concerned with a developing or developed country, and whether or not the data are recent. In a simple correlation analysis we do, however, find statistically significant (at the five and ten percent level respectively) negative correlations between the average year of the study and the dummy for use of cross-section data (-0.52), and the year and the dummy for use of industry level data (-

0.35). This suggests that studies using older data tend to be those which use cross-section and industry level data, which may be due to the availability of better and more disaggregated data for more recent research, as discussed above. There is no statistically significant correlation between the use of industry level and cross-section data, however, indicating that the availability of more dis-aggregated data does not necessarily imply that these data are available in longitudinal format. Thus, in terms of the data available, what appears to be important is the question of whether the data are available over a period of time, rather than just a cross section. The availability of more dis-aggregated data at a firm level does not seem to affect the result of productivity spillover studies.

3. Testing for Publication Bias

At least since De Long and Lang (1992) have economists recognised that there may be a tendency among editors of academic journals to publish papers preferably if they reject their null hypothesis, i.e., if they produce statistically significant results. This is frequently referred to as publication bias and has attracted growing interest in the recent economics literature (see, Card and Krueger, 1995, Neumark and Washer, 1996, Ashenfelter et al., 1999). As these papers argue, a meta-analysis provides an opportunity to test for publication bias using the results available from the literature.

Such tests are usually based on the idea that, if there were no publication bias, the *t*-statistic on the coefficient in question should be positively related to the size of the sample used in the analysis (Begg and Berlin, 1988). In the case of studies of productivity spillovers, for example, we would therefore expect that studies based on only a small number of observations should be more likely to find a statistically insignificant spillover effect than studies using large numbers of observations. If there were publication bias present, however, we would see that the *t*-ratio were independent of sample size, since studies based on small samples would be equally likely to produce statistically significant effects. As Begg and Berlin (1988) point out, however, this effect of publication bias is based on the assumption that the true spillover effect in the various studies is unrelated to sample size. While this seems intuitively plausible in the case of a single fixed spillover effect, i.e., if the spillover effect were assumed to be the same across countries and time periods, the assumption of a fixed effect is clearly not appropriate for our analysis, and, indeed, for most studies in economics. The papers included in our meta-analysis are concerned with a variety of host countries with widely different characteristics, and different time periods. It does therefore not appear reasonable to expect the true spillover effect to be fixed across the different studies included, rather, we should assume that the effect is randomly distributed. If that is the case we need to consider whether we would still expect the random effects to have a distribution which is independent of sample size. Following Begg and Berlin's (1988) arguments, we would expect that that is indeed the case. In economic analyses, sample sizes are usually not planned (as they are, for example, in medical research) but depend mainly on the availability of data and computing power. Therefore, as argued by Begg and Berlin (1988) it may be reasonable to assume that the sample size is determined without any meaningful association to the underlying true random effect.

This assumption then allows us to investigate for publication bias by analysing whether there is indeed no meaningful relationship between sample size and spillover effect. We utilise the test proposed by Card and Krueger (1995), which is a simple yet intuitive test of publication bias. As pointed out above, basic sample theory suggests that, loosely speaking, studies with larger numbers of observations should also produce higher *t*-ratios. More precisely, as Card and Krueger (1995) point out, the coefficient of a regression of the log of the absolute value of the *t*-ratio on the log of the square root of the degrees of freedom should be equal to 1. This suggests a straightforward test for publication bias, namely, estimate the said regression and examine the size of the coefficient. This is what we set out to do in this section.

We use the same data set as used for the meta-analysis in Section 2, excluding the two unpublished studies. Fig. 1 shows the relationship between the absolute value of the estimated *t*-statistics and the square root of degrees of freedom in the included studies. We would expect a positive relationship between the estimated *t*-statistics and degrees of freedom, which does not appear to be the case for the data displayed in the graph. It is not obvious from Fig. 1 whether there is any relationship, the scatter of points appears to be most closely fitted by a horizontal line. Note that this graph clearly shows the two results which are outliers in our sample and which may blur the overall relationship. In order to take account of this, we also graphed the observations excluding the two outliers in Fig. 2. Again now clear-cut relationship is apparent.

Fig. 1 and 2 here

To examine this issue in more detail we regress the log of the absolute value of the *t*-statistics on the log of the square root of degrees of freedom (*lsrdf*), controlling for other meta-independent characteristics as above. We then perform a simple *t*-test on the coefficient on *lsrdf* to check whether the hypothesis that the coefficient is equal to 1 can be rejected. The results of different specifications of this regression are reported in Table

4. As in the estimations in the previous sections, we present results for the total sample in Columns (1) to (4) and for the sample excluding the two outliers in columns (5) to (8).

Table 3 here

Inspection of the *t*-statistics reported in the table shows that we can reject the hypothesis of the coefficient on *lsrdf* being equal to 1 for two out of four specifications of the estimations reported in columns (1) to (4), and for all estimations presented in columns (5) to (8). Thus, our analysis provides at least some evidence that publication bias may be present, i.e., that studies of productivity spillovers are more likely to become published if they report statistically significant effects of foreign presence on productivity in domestic firms.

Card and Krueger (1995) also suggest that a regression of the coefficient in question on its standard error may provide evidence as to whether publication bias is present. In theory, one would expect no systematic relationship between these two variables but if publication bias is present, a *t*-ratio will have to exceed (roughly) 2 in absolute value, in which case there may be a positive relationship between the coefficient and the standard error (since $t=b/\mathrm{SE}$). Performing this regression on all observations in our sample yields the following regression (heteroskedasticity-autocorrelation consistent standard errors in parentheses):[8]

$$b_j = \underset{(0.101)}{-0.051} + \underset{(0.090)}{3.134}SE_j \qquad (2)$$

where the coefficient on *SE* is statistically significant at the 1 percent level and the R-squared equals 0.78.

[8] Exclusion of the two outlying observations yields qualitatively and quantitatively similar results.

Arguably, as Card and Krueger (1995) point out, the above equation may not be appropriate since different studies estimate different functional forms and the coefficients and standard errors obtained may therefore not be comparable. To overcome this problem, they estimate elasticities based on the regression coefficients and sample means. Unfortunately, we are not able to do the same because the majority of studies of productivity spillovers do not provide information on sample means of productivity and foreign presence. To take account of the above problem we, therefore, decided to split our sample into papers using linear and those using log specifications and estimate regression (2) separately for both samples. Only five studies, however, use a log specification which does not allow us to run a meaningful regression on that sample. Estimating the regression on the sample including the twelve remaining published papers which use linear specifications (yielding 16 observations) gives the following result:[9]

$$b_j^{lin} = \underset{(0.129)}{0.029} + \underset{(0.096)}{3.098} SE_j \qquad (3)$$

with an R-squared of 0.82.

Thus, while these results have to be interpreted with some caution, they may lend further credence to the claim that there is indeed evidence of publication bias in the literature on productivity spillovers which we have included in our sample.

4. Conclusion

A substantial body of literature analysing whether or not there are productivity spillovers from the presence of multinational companies to domestic firms in host countries has developed over the past 25 years, but these studies produce mixed empirical

[9] Again, excluding the two outliers does not change the result qualitatively or quantitatively.

results. Our meta-analysis of the results published or circulated in a number of studies in this area shows that some aspects of the research design may affect the results of that study. We find that, on average, cross-sectional studies report higher coefficients of the effect of foreign presence than panel data studies, and that the definition of the foreign presence variable included in the studies seems to affect the results obtained. We also find some evidence that suggests there may be publication bias in the studies that we reviewed.

Our analysis has implications for future analyses of spillover studies. As pointed out above, these have become more ubiquitous in the last decade, possibly because of the greater availability and quality of data to study such effects. Our meta-regression analysis suggests that the results of productivity spillover studies do not seem to be affected by whether the studies use sector or firm level data, but that it is important whether the data used are cross-sectional or panel data. Specifically, cross sectional studies may overstate the spillover effects of MNCs on domestic productivity because they do not allow for other time-invariant firm or sector specific effects, which may impact on the relationship between multinationals and productivity, but for which the researcher does not have any information. For example, high productivity sectors or firms may attract the location of multinationals in the same sector yielding a positive relationship between these even without spillovers taking place. Panel data would allow the researcher to control for such factors.

Also, our findings point to the need for researchers to take care in defining foreign presence in a sector, as different measures may yield different evidence as to whether or not productivity spillovers from multinationals take place. Assuming that data are available, it seems to be preferable to use alternative measures of foreign presence before concluding on whether indigenous firms benefit from their foreign counterparts through spillovers.

Finally, the possibility of publication bias in the literature suggests that studies of productivity spillovers are more likely to get published if they find statistically significant results for the presence of either positive or negative spillovers. This implies that the currently available published literature may not be completely representative of what may have thus far been found on the topic. An implication is that some studies, if they find statistically insignificant results and are unlikely to be published, may never make it to the scrutiny of the public eye.

Table 1
Papers on productivity spillovers included in the meta-analysis

Author(s)	Country	Year	Data	Aggreg.	MNC Measure	Obs.	*t*-stat	Result
Caves (1974)	Australia	1966	cs	industry	empl	22	3.2	+
Globerman (1979)	Canada	1972	cs	industry	output	42	1.5	+
Blomström & Persson (1983)	Mexico	1970	cs	industry	empl	215	3.1	+
Blomström (1986)	Mexico	1970/1975	cs	industry	empl	145	3.1	+
Haddad & Harrison (1993)	Morocco	1985-1989	panel	firm & ind.	assets	11772 / 440	-0.1 / -5.9	-
Blomström & Wolff (1994)	Mexico	1970/1975	cs	industry	empl	20	4.1	+
Kokko (1994)	Mexico	1970	cs	industry	empl	216	3.5	+
Kokko (1996)	Mexico	1970	cs	industry	empl	156	2.4	+
Kokko et al. (1996)	Uruguay	1990	cs	firm	output	159	0.9	?
Aitken & Harrison (1999)	Venezuela	1976-1989	panel	firm	assets	32521	-3.6	-
Blomström & Sjöholm (1999)	Indonesia	1991	cs	firm	output	13663	4.4	+
Chuang & Lin (1999)	Taiwan	1991	cs	firm	assets	8846	27.7	+
Sjöholm (1999a)	Indonesia	1980-1991	cs	firm	output	15670 / 7760 / 2892	19.7 / 4.9 / 3.0	+
Sjöholm (1999b)	Indonesia	1980-1991	cs	firm	output	2892	3.2	+
Djankov & Hoekman (2000)	Czech Re.	1993-1996	panel	firm	assets	340	-3.1	-
Kathuria (2000)	India	1976-1989	panel	firm	sales	108	-4.7	-
Liu et al. (2000)	UK	1991-1995	panel	industry	empl	240	2.1	+
Driffield (2001)	UK	1989-1992	cs	industry	sales	103	1.3	+
Girma et al. (2001)	UK	1991-1996	panel	firm	empl	11406	0.3 / -1.1	?
Barrios (2000) (unpubl.)	Spain	1990-1994	panel	firm	output	3073	-1.0	?
Flores et al. (2000) (unpubl.)	Portugal	1992-1995	panel	firm	output	36	1.7	?

Table 2
Results of meta-regression
Dependent variable: *t*-statistic

	Including outliers				Excluding outliers			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Square root of degrees of freedom	0.030 (0.037)	0.052 (0.037)	0.034 (0.035)	0.039 (0.038)	-0.014 (0.012)	0.003 (0.016)	-0.011 (0.013)	-0.004 (0.019)
Dummy = 1 if data are industry level		0.619 (3.417)		-2.051 (4.895)	-	-0.344 (2.020)	-	-0.922 (2.297)
Dummy = 1 if data are cross-section		11.169 (3.692)***		12.422 (4.612)**	-	5.047 (1.479)***	-	4.067 (1.399)***
Dummy = 1 if data are for developing country		-4.511 (3.050)		-4.304 (2.777)	-	-1.891 (1.187)	-	-0.912 (0.969)
Average year of study period		0.229 (0.182)		0.291 (0.205)	-	0.043 (0.090)	-	0.064 (0.067)
Dummy = 1 if dependent variable is output growth			-4.474 (3.862)	-3.962 (2.973)	-	-	1.262 (1.378)	0.590 (1.085)
Dummy = 1 if dependent variable is other definition			-4.973 (5.301)	-1.333 (2.290)	-	-	-1.063 (1.628)	-0.976 (1.410)
Dummy = 1 if foreign presence measured as output share			0.806 (2.193)	-3.465 (3.117)	-	-	-0.343 (1.046)	-1.606 (1.418)
Dummy = 1 if foreign presence measured as other definition			0.601 (5.514)	1.221 (3.759)	-	-	-4.376 (1.584)***	-3.100 (1.278)**
Constant	1.627 (1.175)	-457.614 (363.216)	3.012 (1.686)*	-577.099 (409.476)	1.996 (0.752)**	-86.048 (179.265)	2.708 (0.581)***	-125.963 (132.312)
# of obs.	25	25	25	25	23	23	23	23
F	0.67	2.74	0.90	4.07	1.33	4.11	6.76	11.81
R^2	0.05	0.53	0.16	0.63	0.05	0.55	0.49	0.69

Notes: heteroskedasticity-autocorrelation consistent standard errors in parentheses.

***, **, * denote statistical significance at the 1 per cent, 5 per cent, 10 per cent level respectively

Table 3
Results of meta-regression to test for publication bias
Dependent variable: log of absolute value of *t*-statistic

	Including outliers				Excluding outliers			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log of square root of degrees of freedom	-0.077 (0.330)	0.174 (0.529)	-0.215 (0.403)	0.232 (0.485)	-0.326 (0.311)	-0.293 (0.484)	-0.439 (0.392)	-0.135 (0.435)
Dummy = 1 if data are industry level		0.514 (1.096)		0.727 (1.506)		0.232 (0.901)		1.217 (1.375)
Dummy = 1 if data are cross-section		1.222 (0.794)		1.615 (1.035)		0.180 (0.612)		-0.398 (1.142)
Dummy = 1 if data are for developing country		0.506 (0.863)		0.322 (0.621)		1.124 (0.617)*		0.843 (0.671)
Average year of study period		0.016 (0.040)		0.006 (0.052)		-0.003 (0.033)		-0.027 (0.053)
Dummy = 1 if dependent variable is output growth			-0.546 (0.746)	-0.317 (0.966)			0.146 (0.733)	0.562 (1.026)
Dummy = 1 if dependent variable is other definition			0.379 (0.589)	0.440 (0.822)			0.911 (0.567)	0.778 (0.860)
Dummy = 1 if foreign presence measured as output share			1.100 (1.023)	0.447 (0.961)			0.955 (0.889)	1.449 (1.402)
Dummy = 1 if foreign presence measured as other definition			1.023 (0.823)	1.434 (0.824)			0.505 (0.525)	0.560 (0.577)
Constant	1.119 (0.817)	-31.975 (79.413)	1.097 (0.829)	-13.564 (103.085)	1.702 (0.784)**	6.280 (64.764)	1.510 (0.810)	52.092 (104.836)
# of obs.	23	23	23	23	21	21	21	21
t-stat (h_0: β=1)	-3.26	-1.56	-3.01	-1.58	-4.27	-2.67	-3.67	-2.61
F	0.05	0.71	1.31	3.76	1.10	0.97	1.37	7.93
R^2	0.01	0.19	0.14	0.34	0.08	0.27	0.19	0.38

Notes: heteroskedasticity-autocorrelation consistent standard errors in parentheses.

***, **, * denote statistical significance at the 1 per cent, 5 per cent, 10 per cent level respectively

Fig. 1
Relation of *t*-statistics to log of degrees of freedom (including outliers)

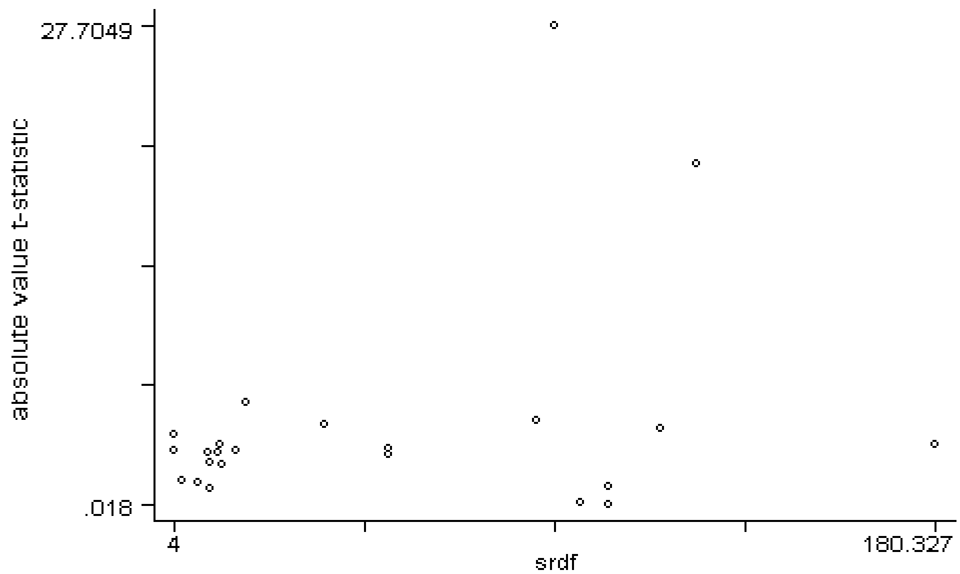
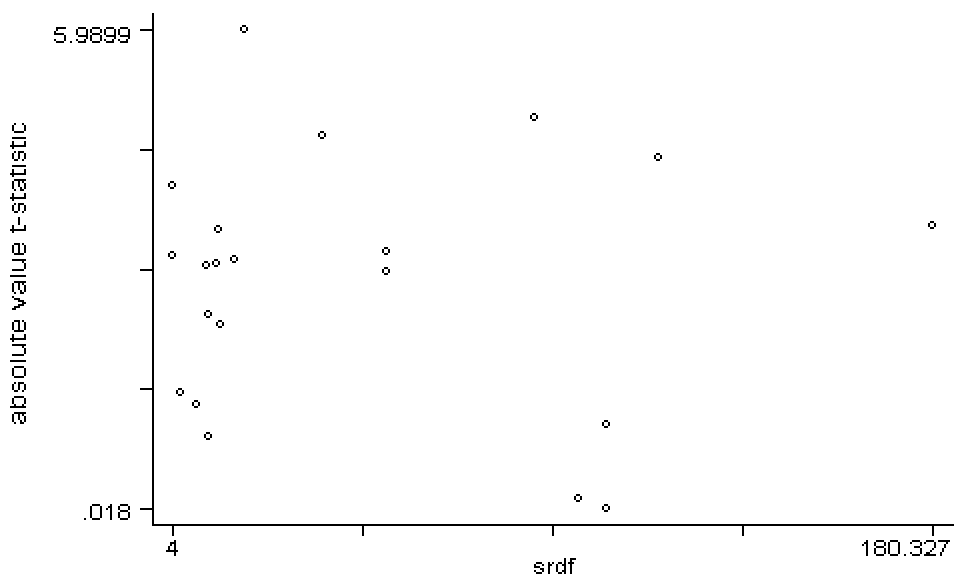


Fig. 2
Relation of *t*-statistics to log of degrees of freedom (excluding outliers)



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